PROJECT ID: eems019

U.S. DEPARTMENT OF ENERGY

SMARTMOBILITY

Systems and Modeling for Accelerated Research in Transportation

Smart Urban Signal Infrastructure and Control

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2017 ANNUAL MERIT REVIEW
JUNE 19, 2018

Argonne NATIONAL LABORATORY | INL Idaho National Laboratory | BERKELEY LAB | OAK RIDGE National Laboratory | NREL NATIONAL RENEWABLE ENERGY LABORATORY

ENERGY EFFICIENT MOBILITY SYSTEMS PROGRAM INVESTIGATES

MOBILITY ENERGY PRODUCTIVITY

THROUGH FIVE EEMS ACTIVITY AREAS

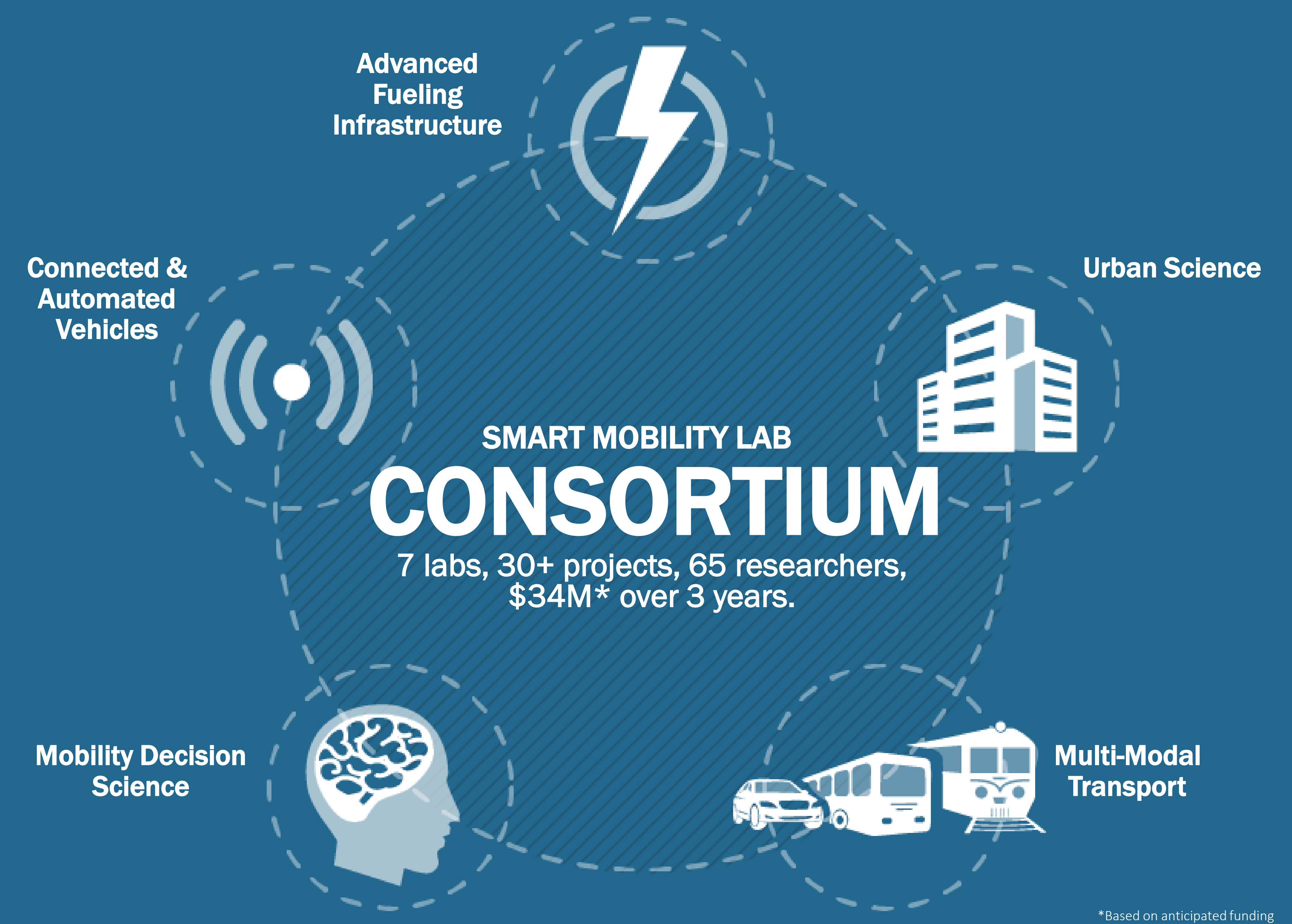
Advanced R&D Projects

Living Labs

Smart Mobility Lab Consortium

Core Evaluation & Simulation Tools

HPC4Mobility & Big Transportation Data Analytics


Advanced Fueling Infrastructure
Connected & Automated Vehicles
Urban Science
SMART MOBILITY LAB
CONSORTIUM
7 labs, 30+ projects, 65 researchers, $34M* over 3 years.
Mobility Decision Science
Multi-Modal Transport
*Based on anticipated funding

Overview

Timeline

- Project start date: 10/1/2016
- Project end date: 9/30/2019
- Percent Complete: 55%

[Deliverable complete for Quarter 2 in FY18]

Budget

- Total project funding:
  - DOE Share: $310K for FY18
  - Contractor share: NA
- Fund received in FY17: $270K
- Fund for FY18: $310K
  - ORNL Share: $200K
  - PNNL Share: $110K

Partners

- Pacific Northwest National Laboratory
- National Renewable Energy Laboratory

Barriers

- Accurately measuring the transportation system-wide energy impacts of connected and automated vehicles (CAVs),
- Computational difficulty of accurately simulating and optimizing large- scale network of signalized intersections,
- Implementation of traffic control algorithms in a mixed traffic environment of legacy and CAVs.

Relevance/Objectives

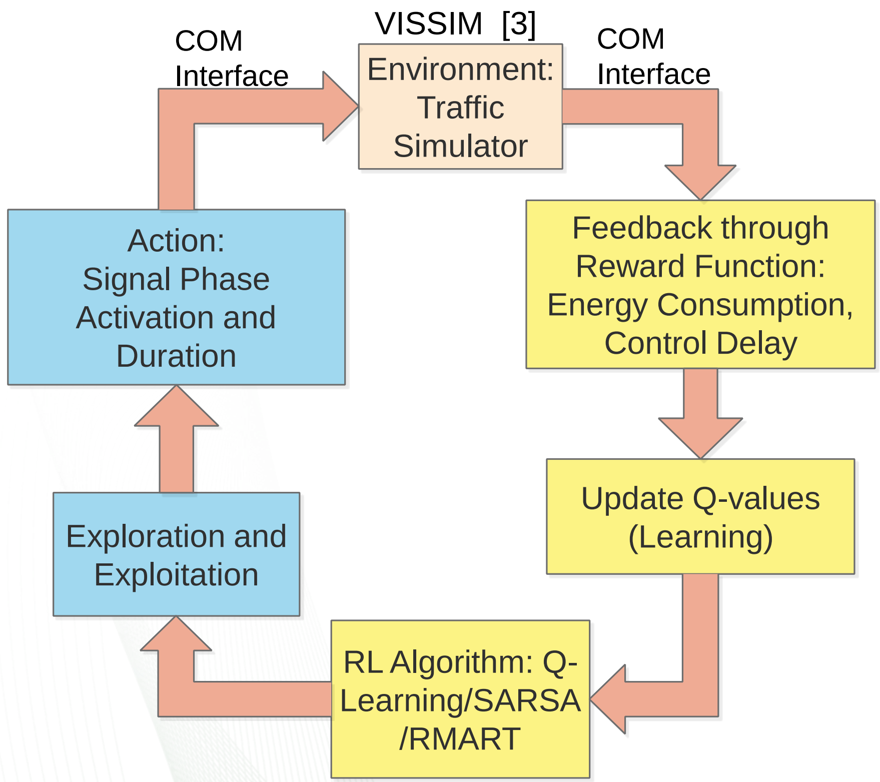
- Overall objectives
  - Investigate the impact of traffic signal systems in an Automated, Connected, Electric, and/or Shared (ACES) environment focusing on **mobility**, **energy**, and **productivity**
  - Develop robust and scalable signal control schemes leveraging data and connectivity with the goal—*maximizing mobility with minimal energy*
- Objectives for FY18
  - To develop signal control algorithms to minimize energy consumption from urban signalized transportation networks,
  - To understand the impact of the market share of CAVs on the performance of the developed algorithms through sensitivity analysis,
  - To identify potential sensor technologies that enables the data and communication environment for real-world implementation.
- Impact
  - Provide an assessment of the impact of signal control optimization in an ACES environment in terms of energy minimization, and mobility improvement
  - Estimate the impact of CAV market-share on signal system performance

Milestones and current status FY18

Timeline	Milestone(s)	Deliverable(s)	Status
FY18Q1	Setting energy-based objectives in signal control schemes	No Deliverable	**NA**
FY18Q2	Building the mathematical framework of control algorithms and base simulation	A report on stochastic control of traffic signal systems	**Complete**
FY18Q3	Implementation of stochastic control theory based signal scheme and initial results for a corridor	No Deliverable	On Track
FY18Q4	Development of machine-learning based signal control with energy and mobility objectives	A paper with results from a real-world test network using VISSIM-traffic simulator tool—demonstration of energy minimization by signal control	On Track (**Obtained initial results**)
FY19	Develop distributed control for a network of signalized intersections—scalability; Develop fault-tolerant signal systems	Report on the demonstration of scalability for large networks	

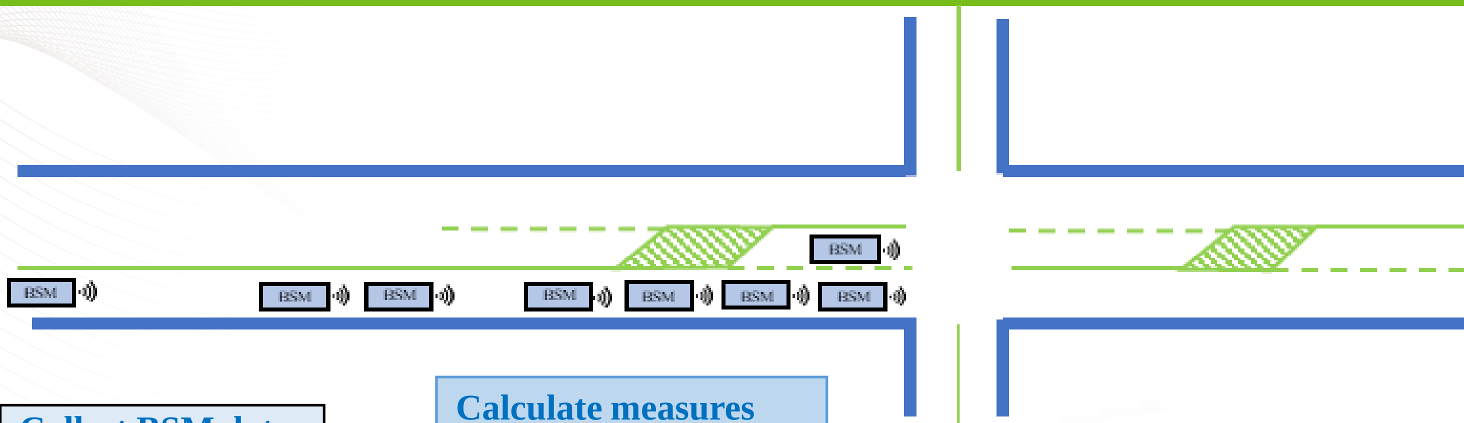
Approach: Reinforcement Learning-Overview

- Signal control problem can be formulated as Markov-Decision-Process (MDP) and can be solved using reinforcement learning (RL)
- RL technique does not need prior information on transition probabilities—no value function is needed
- Near optimal solution is possible
- RL can theoretically reach optimal solution as learning converges [1, 2]
- Connected vehicle environment provides the data and feedback capability to execute RL-based signal control



[1] A. Gosavi, *Simulation-Based Optimization: Parametric Optimization Techniques & Reinforcement Learning (2nd Edition)*. Springer, 2015.
[2] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction (2nd Edition)*, vol. 1. Cambridge Univ Press, 2018.
[3] https://www.ptvgroup.com/en-us/solutions/products/ptv-vissim/

Approach: Reinforcement Learning-Data



Collect BSM data
1. Vehicle ID
2. Speed
3. Acceleration
4. Position

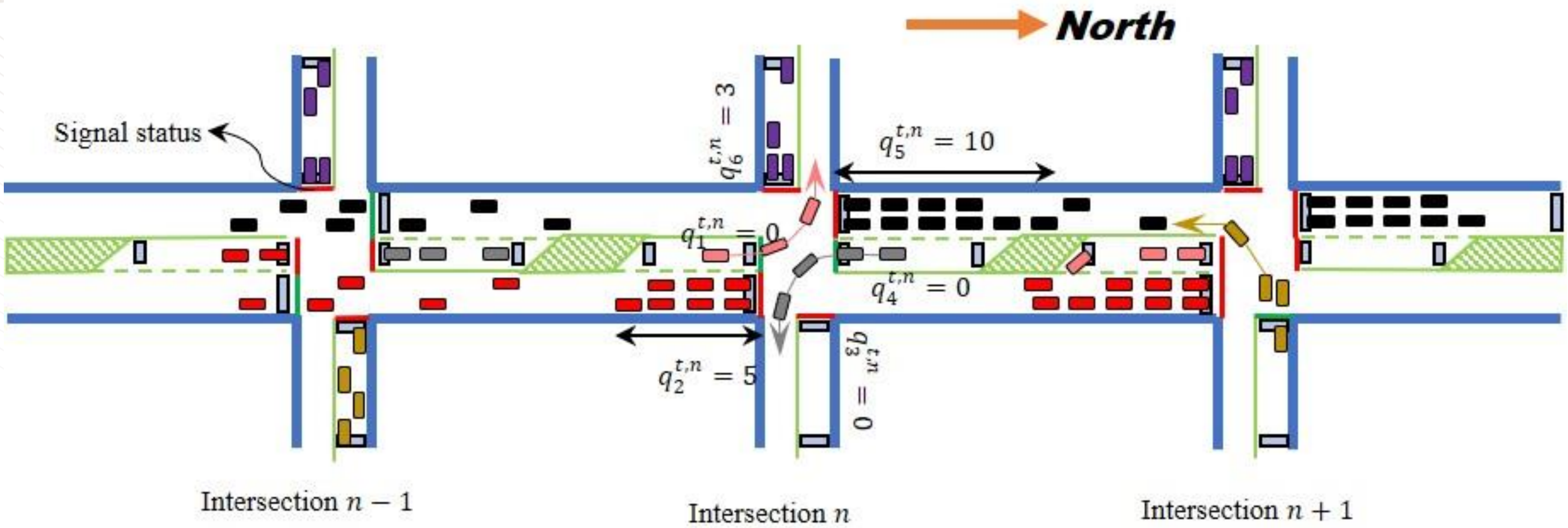
Calculate measures
1. State of the System,
2. Control delay,
3. Energy consumption

State, Rewards + Q-values

RL-Signal control

CV environment facilitates communication platform between vehicles, vehicle to infrastructure and infrastructure components through vehicle-to-vehicle (V2V), V2I and I2I communication. The RL algorithm leverages V2I and I2I communications to ensure the information flow among the agents. Using V2I communication, vehicles continuously broadcast their status, such as speed, acceleration, position to an agent through BSM. Using the shared information from CVs, an agent determines the number of vehicles stopped in a queue based on their speed and acceleration.

Approach: Reinforcement Learning-Traffic State



- All the states in an intersection are presented with different colors. For instance, states corresponding to North-Bound and South-Bound Traffic are represented by red and black arrows respectively,
- We considered both upstream and downstream queues to represent the state of an intersection,
- A clustering based technique is used to make the state-space finite for a tractable implementation.

Approach: Reinforcement Learning-Energy Consumption

m: Vehicle mass,
V: Vehicle speed,
a: Vehicle Acceleration,
ε_i: "Mass Factor" or equivalent transitional mass of the rotating components (i is used to show the gear-dependence),
h: Altitude of the vehicle,
Θ: Slope of the road,
g: Acceleartion due to gravity,
C_R: Coefficient of rolling resistance,
C_D: Drag coefficient,
A: Frontal Area of the vehicle,
ρ_a: Ambient air density,
V_W: Headwind into the vehicle.

Energy consumption is computed based on Vehicle Specific Power (VSP) [1, 2]—The VSP equation differs for different powertrain such as electric and hybrid vehicles

$$VSP = \frac{\frac{\mathrm{d}(E_{kinect}+E_{potential})}{\mathrm{d}t} + F_{Rolling} \times V + F_{Aerodynamic} \times V}{m}$$

$$= V\left[a(1+\varepsilon_i) + g \times \Theta + g \times C_R\right] + \frac{1}{2}\rho_a \frac{C_D \times A}{m}(V + V_W^2) \times V$$

$$VSP_{LDV} = V \times [1.1a + 9.81 * grade(\%) + 0.132] + 0.000302 \times V^3$$

$$VSP_{HDV} = V \times [a + 9.81 * grade(\%) + 0.09199] + 0.000169 \times V^3$$

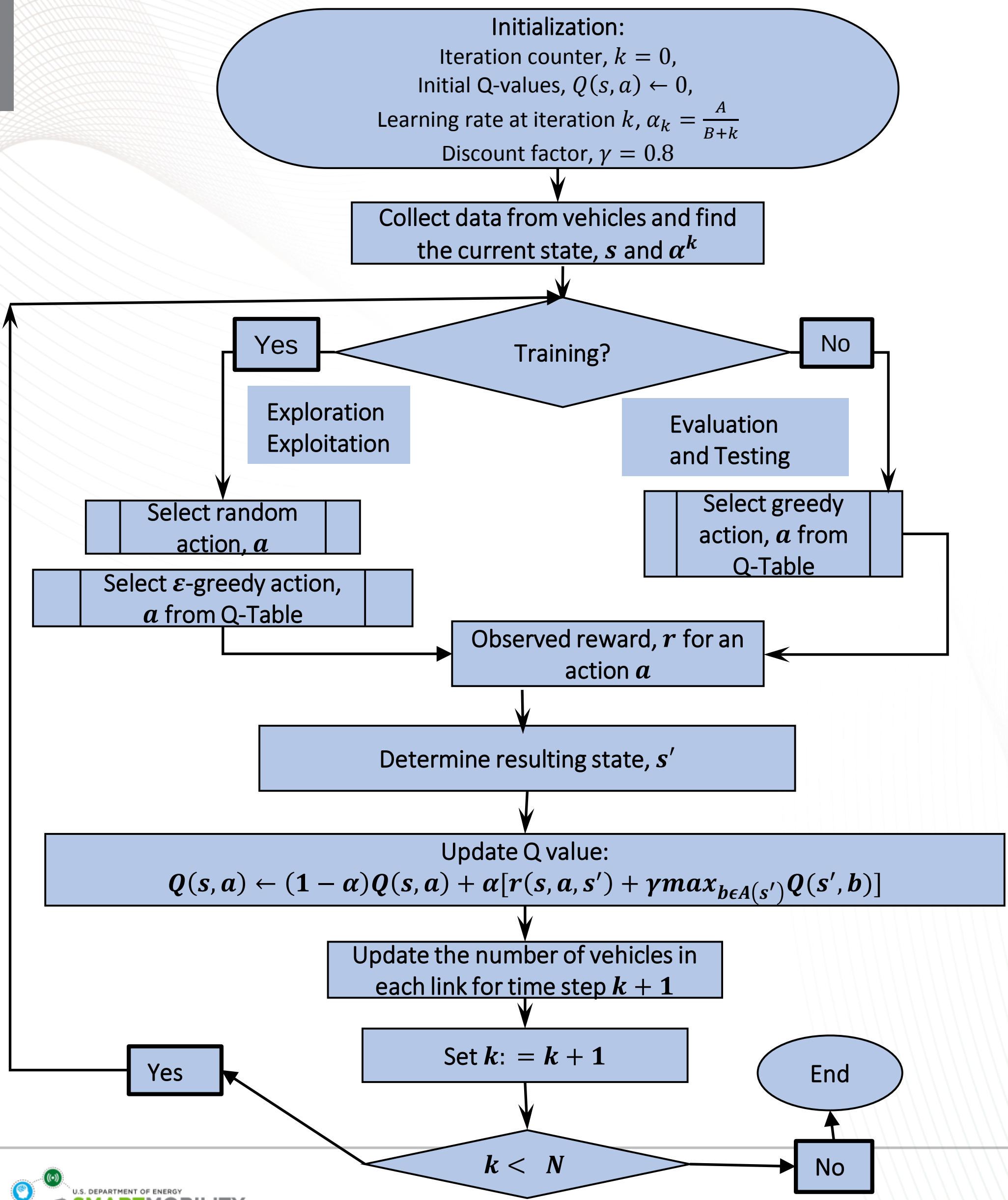
The power requirement, VSP values can be converted into fuel consumption with heat-content computation and brake-thermal, average drive train efficiency values [2, 3]

	Lower Heat of Combustion (Btu/gal)	Lower Heat of Combustion (Btu/lb)	Density (lb/gal)	Carbon Content (g/gal)	Carbon Content (g/lb)
Gasoline	116,100	18,690	6.21	2,421	392
Diesel	128,500	18,400	6.98	2,778	392
Ethanol (E85)	76,300	11,580	6.59	1,560	237

SOURCE: After GREET Program, Argonne National Laboratory, http://www.transportation.anl.gov/modeling_simulation/GREET/.

[1] Jiménez-Palacios, J. L. *Understanding and Quantifying Motor Vehicle Emissions with Vehicle Specific Power and TILDAS Remote Sensing.* PhD dissertation. Massachusetts Institute of Technology, Cambridge, 1999.
[2] National Research Council. *Assessment of fuel economy technologies for light-duty vehicles*. National Academies Press, 2011.
[3] Sovran, G., & Blaser, D. (2006). *Quantifying the potential impacts of regenerative braking on a vehicle's tractive-fuel consumption for the US, European, and Japanese driving schedules* (No. 2006-01-0664). SAE Technical Paper.

Approach: Reinforcement Learning-Control Strategies



Simulation setup for training and evaluation

Parameters	Training	Exploration-exploitation	Testing
Number of runs	400	50	33
Time per run	900s	900s	900s
Action-taking interval	6s	6s	6s
Action taking type	Random	ε – greedy	greedy method

Details can be found at:

SMA B. Al Islam, H. M. A. Aziz, H. Wang, and S. Young, "Minimizing energy consumption from connected signalized intersections by reinforcement learning" submitted to IEEE ITSC 2018 conference.

Approach: Reinforcement Learning-Network Calibration

- Test network from NG-SIM: Detailed vehicle trajectory data on Lankershim Boulevard in the Universal City neighborhood of Los Angeles, CA
- Surface function based calibration approach
- Target metric: Trip travel time

Aerial view of Lankershim Blvd., CA

Start

Sensitivity analysis for all controllable parameters in VISSIM

Select a set of controllable parameters, P

Create a sample of n size based on Latin Hypercube sampling* technique

Run each sample for multiple (e.g., 3 or more) random seeds

Create the surface function:**

$$\min_{\beta} \left\| \sum_{i \in n} \left(MOE_i^{sim} - \sum_{j \in P} \beta_j X_{ij} \right) \right\|$$

Calculate β_j, for all $j \in P$

Find optimal controllable parameters:

$$\min_{x} \left\| MOE^{act} - MOE^{sim} \right\|$$

s.t.

$$x_{min} \leq x_i \leq x_{max}$$

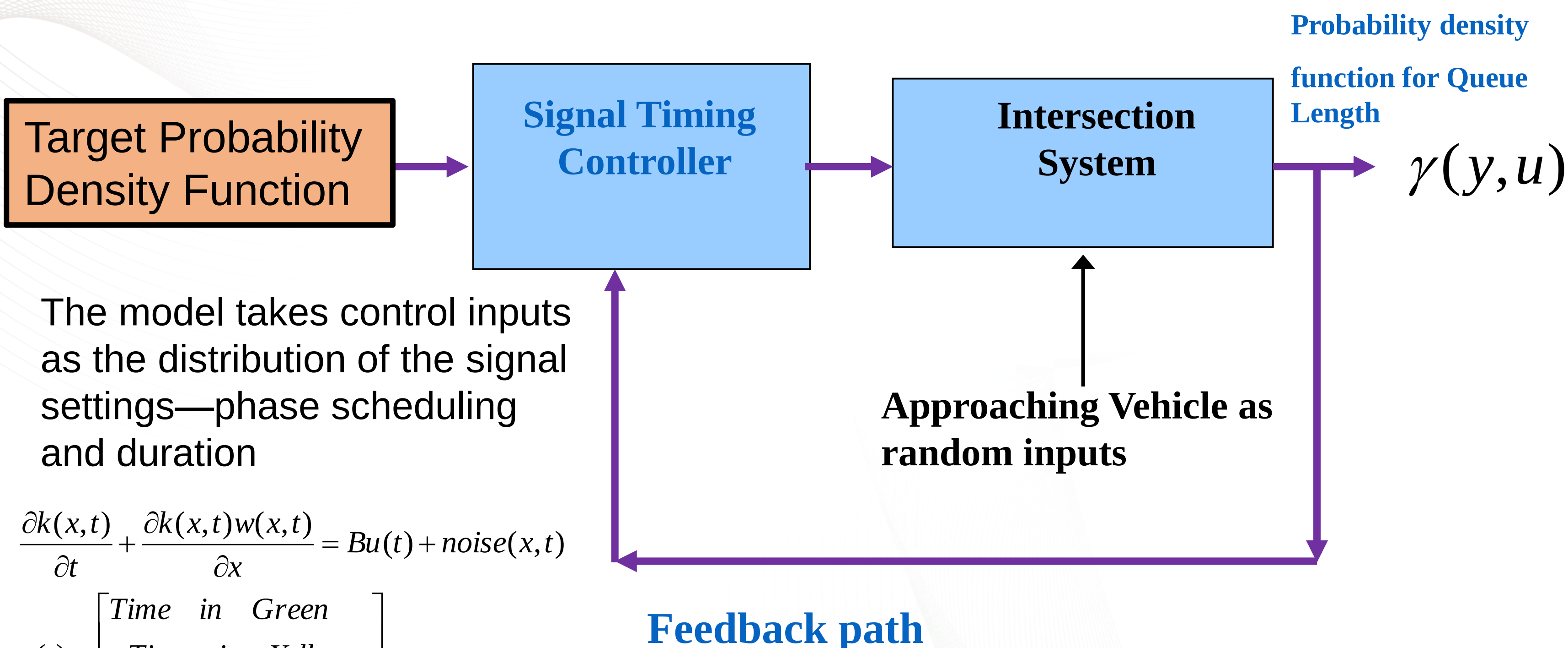
$$MOE^{sim} = \sum_{j \in P} \beta_j X_j$$

End

* Iman, Ronald L. "Latin hypercube sampling." *Encyclopedia of quantitative risk analysis and assessment* (2008).

**Park, Byungkyu, and J. Schneeberger. "Microscopic simulation model calibration and validation: case study of VISSIM simulation model for a coordinated actuated signal system." Transportation Research Record: Journal of the Transportation Research Board 1856 (2003): 185-192.

Approach: Stochastic Control



- The model takes control inputs as the distribution of the signal settings—phase scheduling and duration

$$\frac{\partial k(x,t)}{\partial t}+\frac{\partial k(x,t)w(x,t)}{\partial x}=Bu(t)+noise(x,t)$$

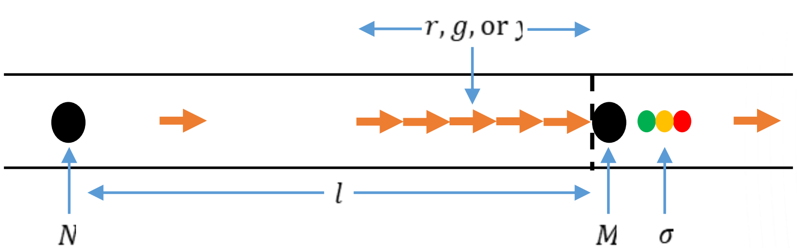
$$u(t)=\begin{bmatrix} Time \quad in \quad Green \\ Time \quad in \quad Yellow \\ Time \quad in \quad Red \end{bmatrix}$$

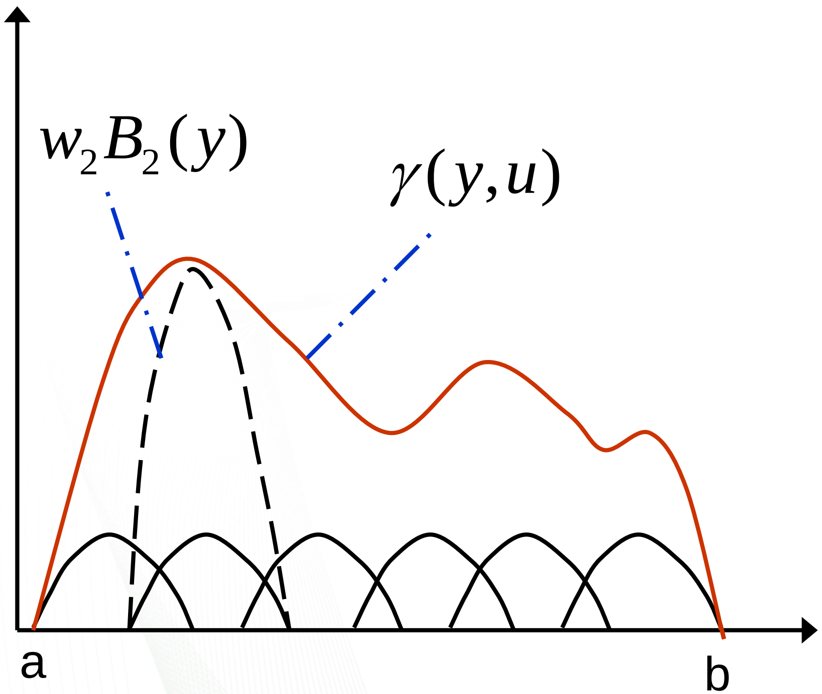
- Systems subjected to random input noises, where control should be performed for output probability density functions

k(x, t): Density of the flow (vehicle/length),
W(x, t): Space mean speed of the flow

H. Wang, Bounded Dynamic Stochastic Distributions Modelling and Control, Springer-Verlag (London) Ltd, March, 2000. (ISBN 1-85233-187-9, total page number: 176).

Approach: Stochastic Control





$\gamma(y,u)$ =queueing length probability density function at time t per controlled by traffic light timing

Technical accomplishments

[1] H. Wang, H. M. A. Aziz, S. Yang and S. Patil, ”Control of Networked Traffic Flow Distribution - A Stochastic Distribution System Perspective”, Proceedings of International Conference on IoT and Machine Learning, **invited publication**, Liverpool, October, 2017,

[2] H. M. A. Aziz, “Learning-based Signal Control Algorithms in Connected And Automated Transportation”-Presented at 2017 INFORMS Annual Meeting, October 22-25, Houston, Texas, USA.

[3] T. Yang, Y. Wan, H. Wang and Z. Lin, Global Optimal Consensus for Discrete-time Multi-agent Systems with Bounded Controls, **Automatica**, Accepted in May 2018.

[4] H. Wang, H. M. A. Aziz and S. Young, Non-Signalized Intersections Control – a Collaborative Fault Tolerant Control Perspective, ASCE International Conference on Transportation and Development, Podium Presentation, Pittsburgh, July, 2018,

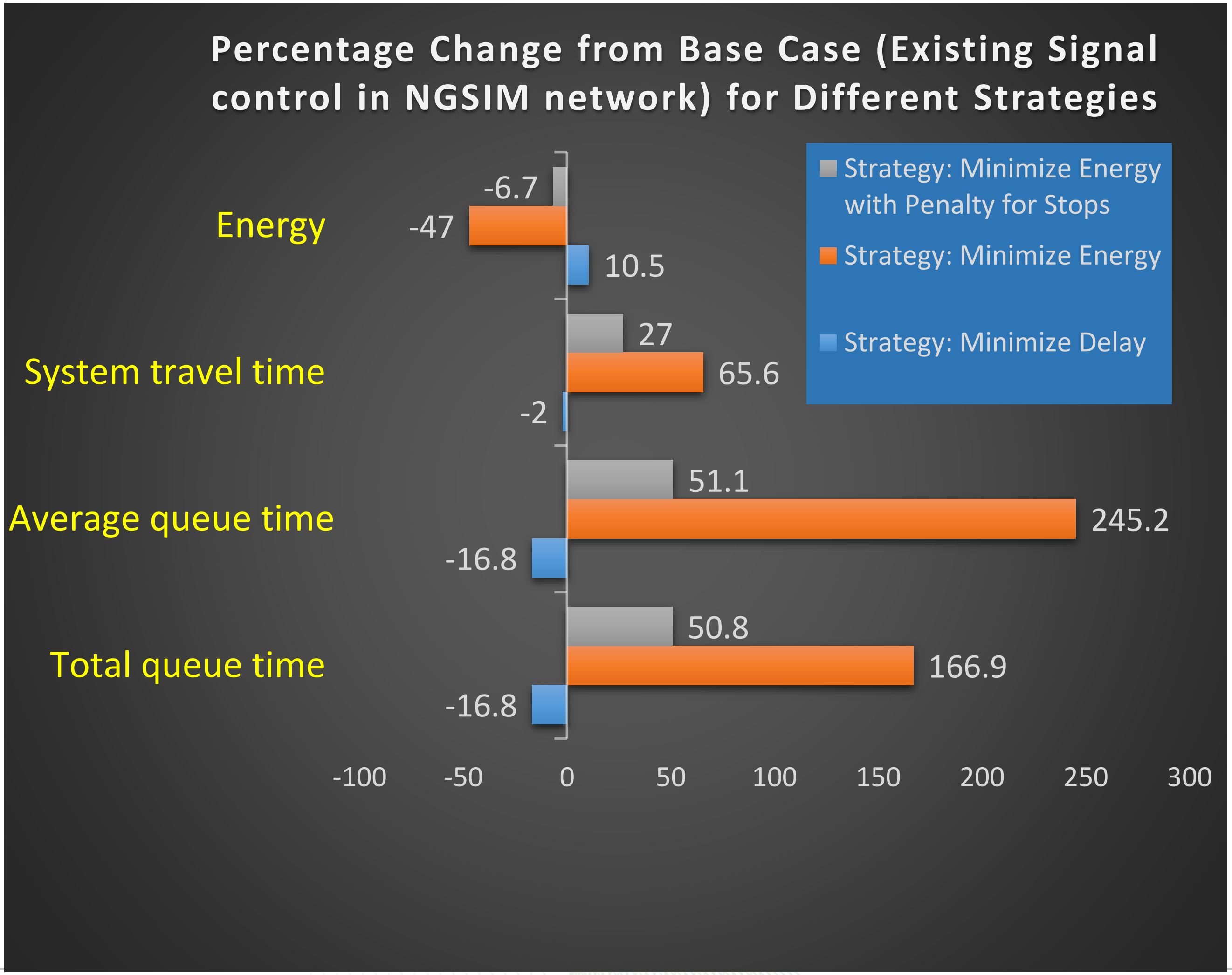
[5] SMA B. Al Islam, H. M. A. Aziz, H. Wang, and S. Young, “Minimizing energy consumption from connected signalized intersections by reinforcement learning” submitted to IEEE ITSC 2018 conference.

Findings: RL Approach

Analysis using RL approach revealed tradeoff between energy and delay.

- Energy minimization strategy yields 47% reduction in energy but at a 65.6% increase in system travel time
- Delay minimization strategy yields 2% decrease in system travel time, but a 27% increase in energy
- Energy minimization with penalty for stops yields 6.7% reduction in energy with 27% increase in system travel time

A balanced approach with desired energy minimization with acceptable delay is required and our developed technique with fine tuned training can achieve that.



Findings: RL Approach

Results from 33 sample runs: mean and bounds are reported at 95% confidence interval

The range of values in the population is determined as follows:

$$\bar{X} - t_{\alpha/2}\left(\frac{s}{\sqrt{n}}\right) < \mu < \bar{X} + t_{\alpha/2}\left(\frac{s}{\sqrt{n}}\right)$$

$\bar{X}$	=	Mean of the sample
s	=	Standard deviation of the sample
μ	=	Mean of the population
n	=	Sample size (= 33)
$t_{\alpha/2}$	=	value from t distribution using degrees of freedom $n-1$

Performance Metric	Estimate	Base-Case	Delay-Min	Energy-min	Energy-Stops Penalty
Completed trips*	Mean	911.12	918.09	488.09	849.73
	Low-Bound	908.1	912.6	451.5	833.7
	Up-Bound	914.2	923.6	524.7	865.8
Number of stops**	Mean	1171.48	1914.64	2332.64	2260.48
	Low-Bound	1159.1	1877.2	2041.5	2147
	Up-Bound	1183.87	1952.1	2623.8	2373.9
Total queue time** (s)	Mean	35885.6	29861.8	95772.9	54131.5
	Low-Bound	35241.8	29146.3	89286.9	49060.1
	Up-Bound	36529.3	30577.4	102259	59202.9
Average queue time**(s)	Mean	34.32	28.56	118.48	51.85
	Low-Bound	33.7	27.9	108.2	46.9
	Up-Bound	34.9	29.3	128.8	56.8
System travel time**(s)	Mean	75087.8	73558.9	124356	95392.9
	Low-Bound	74391.4	72690.3	119117	90511.7
	Up-Bound	75784.1	74427.4	129594	100274
Fuel/Energy-consumption (gallons)	Mean	10.06	11.12	5.33	9.39
	Low-Bound	9.9	11	4.9	9.2
	Up-Bound	10.16	11.3	5.72	9.5

On-going Tasks

- Sensitivity tests for energy-mobility trade-off reward functions
- Assessing impact of advanced technologies such as ***start-stop*** which shuts off the vehicle engine when idling at intersections.
- Assessing impact of traffic state-unobservability (e.g., How to estimate the traffic state when we have a mixed flow legacy and connected vehicles)

Response to Previous Year Reviewers' Comments
(Only the critical comments are addressed)

Question 1: Approach to performing the work

Reviewer 5: "The reviewer stated that it also does not make sense to develop tools until after the majority of critical scenario functions that need to be modeled by the tools is defined. The reviewer cautioned that the current approach schedule has significant risks because it lists tool development and scenario development as concurrent development tasks for FY 2018"

Response: The models that we developed is in fact a framework that can accommodate critical scenarios where additional inputs/variables can be easily added under the proposed modelling framework

Reviewer 6: "The reviewer observed that the project did not address barriers or implementation challenges in the approach and that the approach has the majority of the work biased to the end of the project. …………..The reviewer commented that the modeling activity has the potential to feed into other DOE models, but is not focused on that; the project needs more focus on DOE objectives and needs to start the work quickly in order to finish on time. The reviewer indicated that the project is currently behind schedule due to the approach.

Response: We have defined the barriers based on the suggestion from DOE program managers that reflects the vision of the EEMS program. In the first year of work, we set up goals of the project following our synthetic study report, a significant effort has been made in FY17 to define goals (i.e., smooth traffic with minimized energy usage) and control strategies such as Markov-based control and stochastic control. Our tasks are on track and we have completed all deliverables.

Question 4: Proposed Future Research

Reviewer 3: "The reviewer commented that a better project plan for the future research would be more useful and that a suggestion would be to identify key work packages and milestones to provide high-level visibility to the project activities"

Response: We had several discussion with the program managers and the steering committee members to get the key milestones. The latest quadchart for this project has details.

Partners/Collaborators

- Pacific Northwest National Laboratory
  - Hong Wang (Co-PI), Sagar Patil (Postdoc)
- National Renewable Energy Laboratory
  - Stanley Young (PI for the *Urban Science* pillar and providing directions for the project goals and active tasks)
- Washington State University
  - SMA Bin Al Islam—working as a graduate researcher

Remaining challenges

- Execution in a simulation platform that can handle large scale network of signalized intersections,
- Development of a fault-tolerant systems,
- Identifying potential data-environment for execution of large-scale signal optimization.

Proposed future research

Progress	Timeline	Milestone	Deliverables	Status
On-Going	FY18 Q3	Implementation of stochastic control theory based signal scheme and initial results for a corridor	No Deliverable	On Track
	FY18Q4 4th Quarter	Development of machine-learning based signal control with energy and mobility objectives	A paper with results from a real-world test network using VISSIM-traffic simulator tool	On Track (**Obtained initial results**)
Proposed	FY19Q2	Large-scale implementation of distributed control algorithms	Report/Paper	
	FY18Q3	Fault-tolerant signal control	Report/Paper	
	FY18Q4	Layout on real-world implementation considering data-sensor technologies in an ACES environment	Report	

Any proposed future work is subject to change based on funding levels

Summary

Relevance

- ❑ Develop signal control algorithm in an ACES environment and demonstrate energy savings for real-world test network calibrated and simulated in a state-of-art traffic micro-sim tool—PTV VISSIM

Approach (FY18)

- ❑ Machine learning based techniques:

  - Reinforcement learning with multi-reward functions

- ❑ Stochastic control theory, and multi-objective optimization to integrate energy and mobility objectives

Technical Accomplishments

- ❑ Developed Reinforcement learning based control and a paper is submitted to the IEEE ITSC conf. 2018
- ❑ Five scientific outputs (Journal/Conference) as of May 2018 (see slide 18)

Proposed future research

- ❑ Scalable distributed implementation for a network of signalized intersections
- ❑ Develop fault-tolerant control for signal systems
- ❑ Estimate the impact advanced powertrain on energy minimization at signalized intersections

Any proposed future work is subject to change based on funding levels

Questions/Comments

This research is funded by the Energy Efficient Mobility Systems (EEMS) Program of the Vehicle Technologies Office, Department of Energy and ORNL appreciates the support and guidance provided by DOE program managers